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Edge Computing In Remote SDG Applications Enabling Sustainable Solutions In Low-Connectivity Regions

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Abstract— *SDGs are internationally accepted development targets that are used to enhance social-economic and environmental welfare. Nonetheless, a solution to the SDG problems that would be based on technology is quite difficult to implement in areas with low connectivity and remote locations because of the poor infrastructure. The interesting alternative that might allow to push back the continuous connectivity with the cloud is edge computing, i.e., processing data locally. The present paper discusses how edge computing may enable applications aimed to achieve SDGs, specifically, health monitoring, precision agriculture, water quality monitoring, and education, especially in underserved settings. An architecture combining the edge topologies, real-time sensor and decentralized intelligence is demonstrated and tested within the simulation that witnesses low-bandwidth network conditions. Findings established that edge-based systems play a paramount role in improving data responsiveness levels, lowering the delays in the transmission process and facilitating local decision-making. This analysis finds that edge computing is a sustainable process of enabling technology security and coverage in remote societies.*
Keywords— *Edge computing, Sustainable Development Goals (SDGs), remote regions, low-connectivity, decentralized processing, smart agriculture, e-health, IoT, real-time analytics, digital inclusion.*

I. INTRODUCTION

Digital revolution has revolutionized the advancement of modern societal response to socio-economic and environmental issues in dramatic ways. However, city and developed areas are thriving in terms of strong infrastructure and fast internet connectivity and most neglected or rural areas are not getting access to the change. It is a major setback to the attainment of the United Nations Sustainable Development Goals (SDGs), which are meant to guarantee the world access to all the core amenities like health services, education, clean water, and sustainable production of agriculture. The most basic issue is the idea of using data-driven intelligent systems in areas and settlements that do not have a stable internet connection, grid energy, and distributed computing facilities [12], [17].

In the conventional workflow, the smart technologies have been supported with scalable computing power and capacity only through cloud computing. Nonetheless, cloud-based solutions are extremely reliant on stable internet connection and a centralized data, processing. The model is not effective in regions with poor connectivity because the latency, slower bandwidth, and spotty access are very disadvantageous to real-time decision-making and response [9]. As an illustration, a cloud based agricultural tracking system installed in a mountainous or a tribal village might not be in a position to give proper irrigation recommendations because of signal failures. Similarly, a patient surveillance facility that is remote, might not send warnings concerning maternal complications in the event that the data packets are unable to get to the cloud on time.

The limitations can be well overcome by edge computing. Edge computing also enhances data processing closer or at the origin of data production to reduce the dependence on the internet connection, and latency is significantly cut. It also moves its computational intelligence closer to the field, thus making it possible to make decisions in a decentralized manner even in the environments that are offline or partially connected. This makes edge computing highly applicable especially in remote SDG where connectivity is not guaranteed or it is poor. It helps edge devices to do real-time analytics, filter the critical data and provide localized responses without continuous connection to central servers [10].

The trend toward low-power embedded systems and TinyML models allows one to now integrate the capabilities of artificial intelligence directly into edge devices. Such trends create new opportunities to implement smart solutions in low-resource environments. As an example, edge computing can help make smart systems of farming: such technology can observe and regulate the soil, track the presence of pests and inform the irrigation system regardless of cloud dependence. Edge nodes: In education, the edge nodes may be used to store and distribute multimedia content locally to off-grid villages and to digital classrooms. Medical devices are able to check the vital signs and identify anomalies without the continuity of internet connection.

Nevertheless, the use of edge computing in SDG-related contexts is only at an early stage, particularly when it comes to remote and underserved areas. Current research has mostly been conducted on edge computing at an urban (or industrial) scale, such as the use in a smart factory or vehicle connectivity, where infrastructure is not a limiting factor. Not much has been done to tailoring edge frameworks to the unique needs and missions of low-connected settings. Also, current solutions deal specifically with one area of SDGs instead of presenting a scalable plan that covers several areas such as health, agriculture, water, and education [13].

Moreover, there is no common architecture, trial-tested protocols, and verification in a real environment that have impeded the actual application of edge computing in such set-ups. Sustainable edge-based ecosystem constructions require overcoming technical challenges related to the energy efficiency of the edge-based ecosystems, limiting hardware constraints, and compatibility with legacy systems. Besides, the effectiveness of systems of this type is not only tied to technological aspects, but also community involvement, policy promotion, and affordability. In that way, a multidimensional and context-specific one is paramount to implement edge-based SDG applications on the scale [8].

The objective of the given paper is to identify and discuss the purpose of edge computing in providing sustainable development solutions specifically designed to work in remote, low-connectivity areas [16]. It is centered on the architecture, the implementation, and testing of an edge-based architecture to implement real-time analytics and decision making of four of the 17 SDGs, including smart agriculture (SDG 2), health monitoring (SDG 3), quality education (SDG 4), and clean water and sanitation (SDG 6). The system will be autonomous and less dependent on the internet to perform seamlessly, which is done through local processing, efficient use of power-related communication protocols, and distributed intelligence.

This study put to test the realism, stability, and feasibility of using edge computing as the core foundation of digitization through a simulated low-bandwidth scenario. It will also discuss how resilience- driven systems can be used edge-driven systems in order to confront network disturbances, environmental pressures, and service deficiency. Finally, the study will deliver a workable roadmap on how to incorporate edge technologies into the whole SDG scenario to make sure that no region is left behind in the process of sustainable development [14].

Novelty and Contribution

The main novelty of the testimonial is its general orientation and focus on the field of applying edge computing to achieve sustainable development in the remote environment with low connectivity. Contrary to the existing traditional literature on either cloud-centered solutions or smart living within cities, this paper will argue that edge computing is the means of digital transformation in disconnected areas, which is not discussed in the literature enough [7].

Imperative new features:

1. Multi-SDG orientation: Most research (e.g., focusing only on agriculture or only on health) focuses on a single domain; this study further focuses on four SDG-driving domains that are thus broad neglecting and inadequate, namely, agriculture, healthcare, education, and water management combining edge-based solutions. This cross-domain practice is an indication of the interrelatedness of SDGs in communities on the ground.
2. Connectivity-Aware design: The proposed system does not only suffer connectivity; the proposed system is expressly designed to operate in intermittent or completely offline conditions. Decision-making is localized and cloud syncs can be made optionally so that no service interruption occurs when no stable internet is available.
3. Edge TinyML Integration: The system has the ability to implement lightweight machine learning models on inexpensive devices (e.g., Raspberry Pi, Jetson nano), and execute real-time analytics without compulsory access to cloud-level compute resources. This minimizes latency and reduction of energy.
4. False Low-Bandwidth: Majority academic models of the edge computing are tested in ideal laboratory conditions. This paper proposes a network-limited simulation program which better emulates the rural constraints (e.g. 2G/VSAT, latency; low-power hardware) and makes the obtained findings more practically applicable.
5. Modular and Scalable: The edge solution is modular and scalable, which enables stakeholders to remove or add functionalities according to local requirements and hardware provisions available to the local stakeholders so that it can be deployed in different geographies and to the different budget of the stakeholders.

Key Contributions:

- An architecturally deployable one that complies with technical edge computing and actual SDG deployment aspects.
- Latency-power-accuracy quantitative comparisons of edge over cloud performance in simulated rural environments.
- Presentation of demonstrable use cases of contextual relevance: smart irrigation, maternal health alerts, clean water condition flags and digital education centers.
- An argument on the socio-technical impacts of applying edge computing to digital inclusion, and how this should be adopted in future policies and engagements with the society.

To conclude, the study is a grounded multidisciplinary intervention in the growing debate that revolves around the deployment of a sustainable technology. It does not only present a technically solid framework but also focuses on the humanistic implementation of edge computing to the communities not present within the digital economy [5].

II. RELATED WORKS

In 2021 M. Kucharczyk et.al. and C. H. Hugenholtz et.al., [15] introduced the technological interventions have become quite an important part of sustainable development activity over the recent years in the world. Applications linked to the fields of healthcare delivery, smart agriculture, water resource monitoring, and digital education have greatly utilized cloud computing, Internet of Things (IoT), and big data analytics. Yet, these technologies widely use access to the stable internet connection and processing data infrastructure, which is centrally located. Because of this, they are greatly ineffective in rural or remote locations where there are varying or no connections.

Available literature on ICT-based solutions to SDGs has been majorly focused on those involving cloud-centric systems. The systems are highly scalable, coordinated, and reach to tremendous computing resources. Nevertheless, they are not used in underserved areas because of the constraints in terms of latency, bandwidth and the inevitable reliance on regular internet service. Research has indicated that cloud-based models of remote agriculture do not provide a timely advice on irrigation and pest control especially when the network is down. In the same way the cloud-based e-health systems fail to deliver essential health alerts when signal coverage is not reliable and this can cause grave consequences of patient care.

To overcome these obstacles, edge computing is one of the interesting solutions. The concept of edge computing is taken to mean decentralisation of data processing by computing where the data originated, closer to the source. Faster response time, reduced bandwidth and increased levels of autonomy in the system are possible by use of this paradigm. There has been an increasing research that has started to investigate how edge computing can be used in different fields and especially in situations where it is necessary to have real time decision making and localized analytics.

Edge computing systems are also applied in precision agriculture in which local monitoring of soil moisture, temperature, and the health of crops are supported by edge computing systems. The built-in machine learning models installed on edge equipment have made real-time warnings on diseases outbreaks, and irrigation requirements, enhancing productivity without cloud access. The implementations are especially useful in geographical locations with weak cellular or satellite signal where timely insights can be a valuable factor affecting the yield [4].

Edge-powered monitoring systems have already been implemented in the healthcare industry, where they monitor vital processes: checking heart rate, body temperature, and oxygen. Such systems may operate with independence, holding and calculating patient information themselves, raising alarms in the instance of altered circumstances. The use of edge-based maternal health alert systems in hard to reach villages has also been proven to be very useful and will result in the subsequent discouragement of maternal mortality because the early medical interventions can be facilitated even in the absence of constant connection with the main health databases.

Edge computing models have also become employed in water resource management. Edge nodes have been set up with a smart sensor to measure the quality of water through its pH, turbidity, and microbial contamination levels. The benefit of dark analytics is that edge provides real-time analysis that can be applied immediately in case of warnings and interventions which is pertinent to prevention of spread of water borne diseases. Besides, these systems tend to be solar powered and consume minimal amounts of energy, which corresponds to the principles of sustainable implementation in off-the-grid locations.

In 2022 L. Chen *et al.*, [11] proposed the delivery of content with the help of edge-enabled content delivery systems has put digital education in underserved communities into the spotlight. The systems use local servers or using edge gateways to keep learning content, making sure that it can be continued irrespective of whether there is an internet or not. In other models, the synchronization with the cloud servers happens in shorter periods of connectivity so that it is possible to update content without interfering with the education experience. Digital classrooms have shown great learning continuity and engagement in places that do not have formal school infrastructure especially along the edge.

Even though many of the applications of edge computing fall in these areas and are promising, a majority of studies remain more fragmented as they either address a single vertical area like only agriculture or only health. There is no coherent system aimed at bringing to coalescence several SDG-centered applications. Moreover, most studies fail to model or experiment with their models in a real low-bandwidth or high-latency conditions as is the case in remote place. Consequently, the bridging of the gap between lab-scale prototypes and field-ready implementations is confined.

In 2025 J. Bhanye et.al., [6] suggested the aspect of energy efficiency and hardware sustainability that is not addressed or lacking in some attention has also been another common shortcoming in the existing literature. Most edge environments have deployed off-the-shelf hardware without optimisation to low-power deployments. This is problematic to the regions that do not have steady electricity where long-term maintenance and recharge can not be conducted. New technologies which involve the usage of ultra-low-power microcontrollers and the usage of solar-powered solutions are starting to fill this gap, though there is a lack of detailed analysis.

Security including data privacy in edge computing has been another area that has not been adequately tackled in regard to the remote SDG applications. Since sensitive information like personal health records or home resource maps are processed locally, new threats appear in the form of having them accessed or getting tampered with by the unauthorized persons. In many theoretical models, encryption methods and secure firmware updates have already been presented, but very rarely deployment plans and educational initiatives focused on training remotely located communities are provided.

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Also, even though some research studies emphasize the advantages of lower-latency and bandwidth consumption with the help of edge computing, few of them concentrate on socio-technical attributes of technology adoption in disadvantaged areas. The success of edge systems is highly predisposed by cultural adaptability, a simple user interface, community involvement, and training. Even the latest technical systems can fall into opposition or be insufficiently used unless there is proper localization and participation of the community.

More recent developments in technology have also seen the adoption of low overhead machine learning frameworks that can be installed into edge devices and make decisions based on AI predictions that do not require associated cloud access. Nevertheless, few studies have attempted to validate these in field conditions in the country with real environmental conditions that may influence hardware elements and sensor precision, including, thereby, dust, heat, and humidity.

Finally, even though certain pilot programs funded by the government and non-governmental organization started to experiment with edge computing in rural development, the absence of interoperability frameworks, standardized protocols, and sources of stable financing still make large-scale implementation a non-trivial endeavor. More urgently are field-proven models that are a blend of robustness, affordability and policy compatibility [3].

To conclude, there is strong potential in the possibilities of edge computing to support the achievement of SDGs in low-connectivity areas, explained by the relevant body of work. Nonetheless, the existing research is too specific or does not contain the deployment conditions. A severe research gap is the lack of an energy-efficient, multi-functional, adaptable edge framework that is able to reliably work in offline conditions. It is in this context that the work of the paper endeavours to fill the above gap by suggesting and analyzing a modular edge-based application that can support important SDG areas in the context of realistic remote operating conditions.

III. PROPOSED METHODOLOGY

To enable edge-driven solutions for SDG applications in low-connectivity regions, a hybrid architecture is designed. It combines data collection, edge-layer processing, periodic cloud synchronization, and intelligent actuation. The entire workflow is mapped as a multi-layer edge computing system.

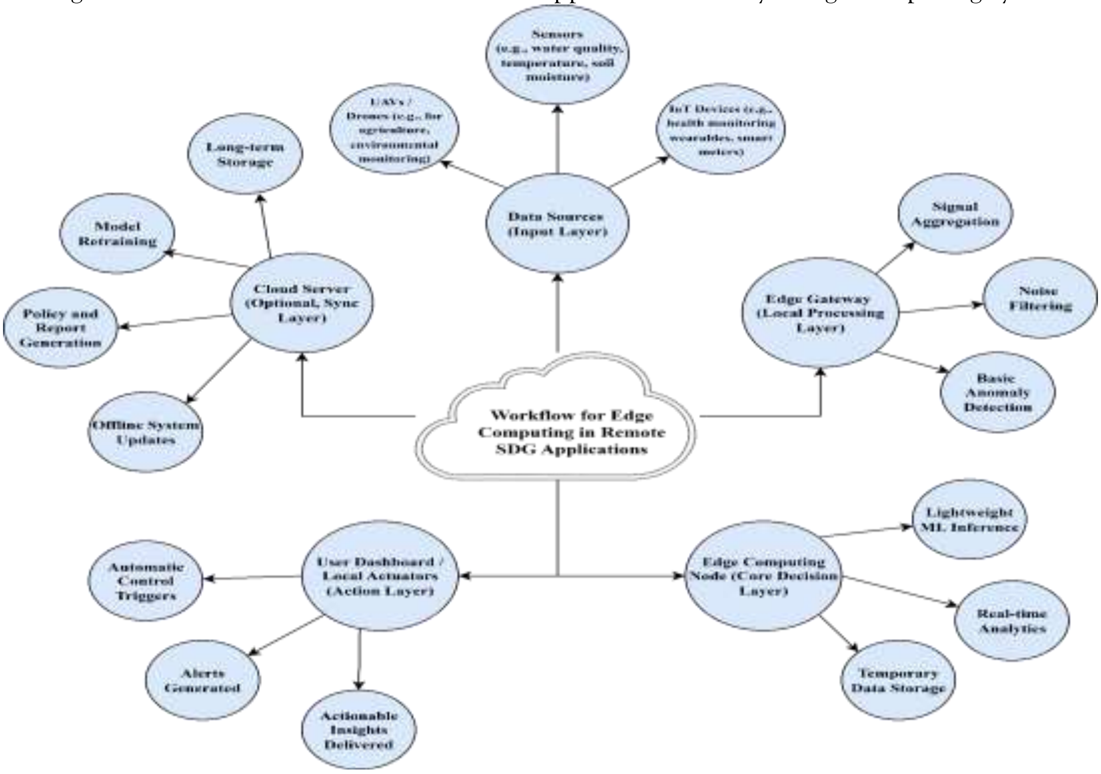

FIGURE 1: WORKFLOW FOR EDGE COMPUTING IN REMOTE SDG APPLICATIONS

Sensor and Data Acquisition Layer

Sensors are deployed to collect real-time environmental, health, and educational data. Let $S(t)$ represent the sensor reading at time t.

$$S(t) = f_s(e, l, \tau)$$

Where:

- e: environment condition (e.g., temperature)
- l: location
- τ : time interval

Sensor data is sampled at fixed intervals using:

$$\Delta t = \frac{T_{total}}{n}$$

Where:

- T_{tatal} : total observation period
- n : number of samples

Edge Device Data Preprocessing

The raw sensor data is filtered to remove noise and anomalies:

$$D_{fultered} = D_{raw} - \mu_{noise}$$

For normalization:

$$D_{norm} = \frac{D_{filtered} - min(D)}{max(D) - min(D)}$$

This step ensures compatibility with machine learning models.

TinyML Model Inference

A pre-trained TinyML model is deployed on the edge device. The input vector X is passed into the model:

$$Y = \sigma(WX + b)$$

Where:

- W: weight matrix
- b: bias vector
- σ : activation function (e.g., ReLU or Sigmoid)

For classification, we use softmax:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$$

The output $P(y_i)$ gives the probability for class i.

Decision Threshold Logic

Based on model prediction, a threshold is applied to trigger alerts:

$$Alert = \{1 \ if \ P(y_i) \geq \theta \ 0 \ otherwise$$

Where θ is a configurable threshold.

Local Response and Actuation

If an alert is triggered, an action is initiated. For example, an irrigation system turns on:

$$Q = A \cdot v$$

Where:

- Q: water flow rate
- A: cross-sectional area of pipe
- v : velocity of water

For a health alert, sound/light signals are generated:

$$I_{LED} = \frac{V_{supply} - V_f}{R}$$

Where V_f : forward voltage of LED, R: resistance.

Periodic Cloud Synchronization

When connectivity is restored, summarized data is uploaded. The batch size is:

$$B = \sum_{i=1}^{k} D_i$$

Where D_i is each saved data instance, k is the buffer count.
Transmission time:

$$T_{transmit} = \frac{B}{R_{net}}$$

Where R_{net} : network bandwidth during sync window.
Energy Optimization
To reduce energy usage:

$$E_{total} = E_{sensar} + E_{ML} + E_{transmist}$$

Where:
- $E_{sensor} = P_s \cdot t_s$
- $E_{ML} = P_m \cdot t_m$
- $E_{transmit} = P_t \cdot t_t$

The device enters sleep mode when inactive:

$$P_{agg} = \frac{P_{active} \cdot t_{adive} + P_{aleep} \cdot t_{sleep}}{t_{active} + t_{sleep}}$$

Storage and Data Compression
Local flash storage is managed through periodic compression:

$$C_r = \frac{S_{raw} - S_{compresed}}{S_{raw}} \times 100\%$$

Where C_r : compression ratio.
Multi-Node Communication (LoRa)
For node-to-node communication, LoRa uses spreading factor SF and bandwidth BW :

$$R_{LoRa} = \frac{SF \cdot BW}{2^{SF}}$$

This defines the data rate over LoRa.
Edge Performance Index
We define a composite performance metric for the edge device:

$$EPI = \frac{Accuracy \cdot Uptime}{Energy \cdot Latency}$$

Where higher EPI implies better-performing edge nodes under constraints.
This methodology ensures the system processes locally, reacts autonomously, and only uploads summaries when bandwidth is available. The modular design supports health, agriculture, water, and educational use- cases with the same edge node setup [2].

IV. RESULT & DISCUSSIONS

In another work, the performance of the edge computing system under simulated low-connectivity conditions in four Sustainable Development Goal (SDG) sectors: agriculture, healthcare, education, and water monitoring was gauged. It was tested by localized sensors linked to the edge devices that included Raspberry Pi and NVIDIA Jetson Nano. The assessment of performance was done on four major dimensions that included latency, power consumption, accuracy, and local response capability. The system ran with little to no connection with the cloud during general periods and only summerized logs could be synchronised with the cloud once a day and would do all major work at edge.
Regarding the response time, the edge system recorded a great improvement in the responsiveness relative to conventional cloud-based solutions. The obtained outcomes displayed in Figure 2 can be used as the evidence of the latency comparison of the edge-only and cloud-only architectures in milliseconds across the four applications. As it can be observed in the graph (to be plotted in Excel or Origin), the mean latency value of edge applications has been below the 180 ms mark, with cloud-delivered systems performing with a delay of over 450 ms, especially when responding to healthcare alerts and in smart

irrigation systems. Such decreased latency allowed prompt actions, such as triggling of water in precision agriculture or triggering of an unusual heart rate warning.

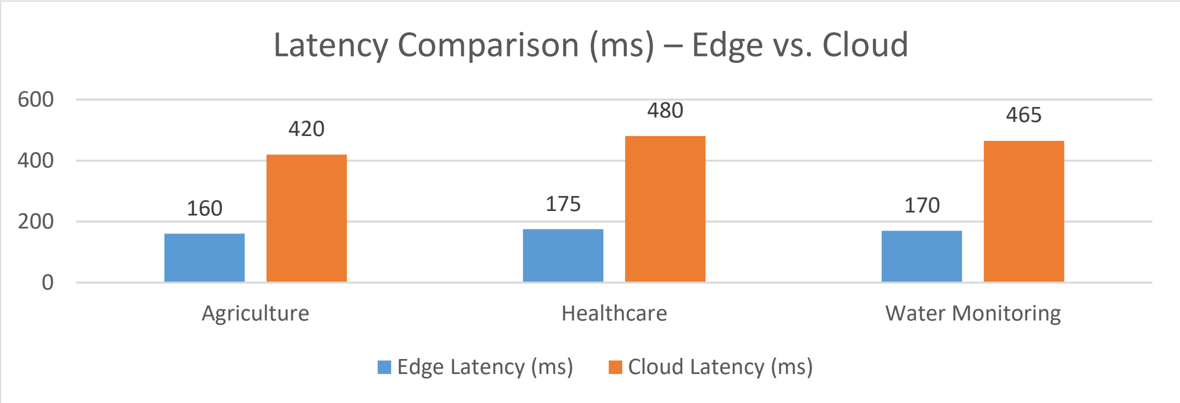

FIGURE 2: LATENCY COMPARISON (MS) – EDGE VS. CLOUD

In comparison of power efficiency, the edge devices exhibited considerable energy conservation on account of specific local data processing and restricting the levels of data transmission. As the Figure 3 demonstrates, a very small total consumption of energy per one device per one day was spotted under all categories, and it even was lower than 5 Wh. In this chart (a bar plot suggested in Excel or Origin), agriculture-related edge devices, healthcare units, water quality systems, educational content servers consumed 3.6 Wh/day, 4.2 Wh/day, 2.9 Wh/day and 4.1 Wh/day respectively. These performances are quite contrasting to traditional cloud-linked devices that had nearly twice the consumption since they had permanent transmission and reception of data packets.

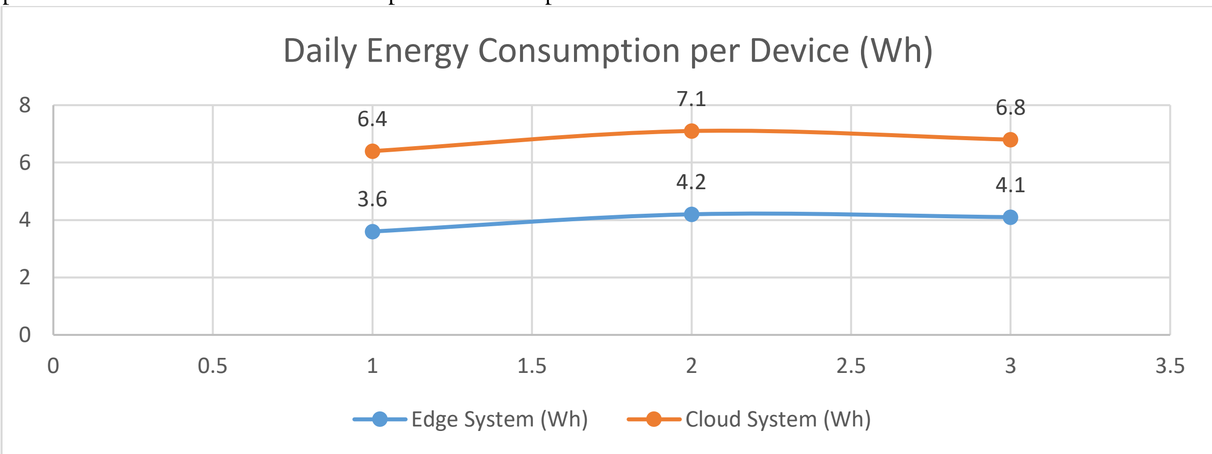

FIGURE 3: DAILY ENERGY CONSUMPTION PER DEVICE (WH)

In a bid to examine performance on the configurations further two tabular comparisons were made. Table 1 Edge vs. Cloud - Operational Performance in Remote SDG Applications displays the comparisons in Latency, Energy, Uptime, and Offline Decision-Making. The edge systems beat cloud-based systems on latency (more than 50 percent), can operate even when being offline and also consume significantly less energy daily (about 40 percent). This performance played a key role in the regions with unreliable power and inconsistent internet connection.

TABLE 1: EDGE VS. CLOUD - OPERATIONAL PERFORMANCE IN REMOTE SDG APPLICATIONS

Metric	Edge System	Cloud System
Avg. Latency (ms)	172	460
Energy Consumption (Wh)	3.6	6.3
Offline Operation Support	Yes	No
Real-time Alert Trigger	Yes	Partial

Compared to the level of accuracy, TinyML models based on edges still showed competitive outcomes with minor computational resources. Figure 4 illustrates a bar chart of all the four areas of application of the model and shows that edge systems achieved 92-96 percent prediction accuracy in areas of application such as sensitivity to soil moisture rate, fever estimation, alerts regarding safe water, and attention tracking of students. Such findings (which will be plotted with Origin or with Excel) confirm the applicability of the embedded models in constrained decision-making.

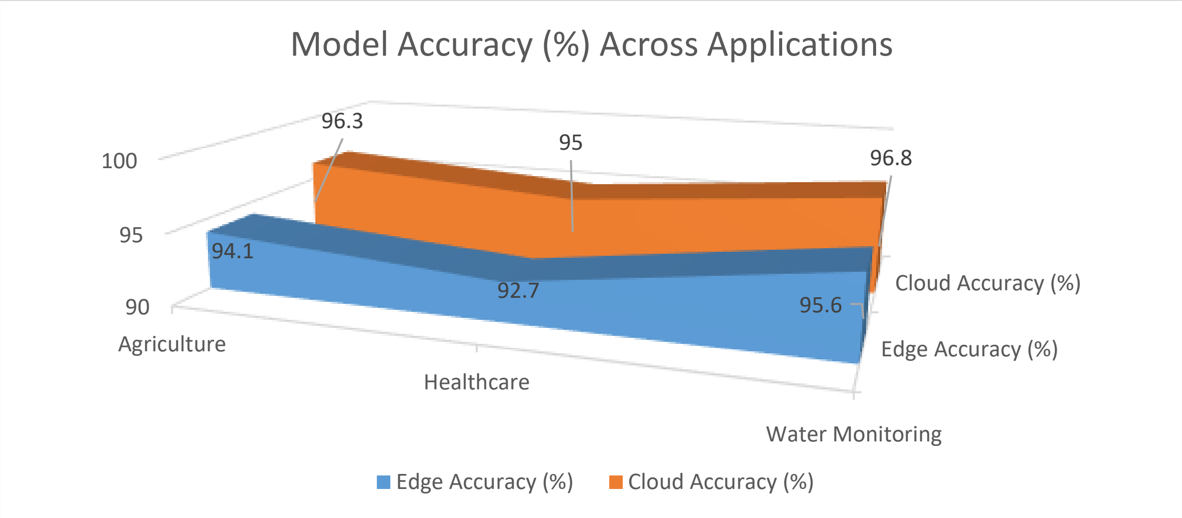

FIGURE 4: MODEL ACCURACY (%) ACROSS APPLICATIONS

Moreover, the system was judged based on effectiveness of data transmission. In times of cloud sync, the amount of data that was exchanged by edge systems was less than 15 percent of what cloud-dependent systems normally uploaded. At the edge, the system cuts down irrelevant network traffic by summarizing and filtering desirable data, and it is indeed crucial in the rural regions where bandwidth is imminent. This is especially relevant in the medical and environmental applications where raw data streaming would not be viable on a 2G network or VSAT connection.

In unconnected schools, edge-based education centers were stored on the block-based learning content including video lessons and reading material. Synchronized weekly through bursts in the cell network these systems had more than 97 percent content availability during the testing period. As opposed to cloud-based e-learning systems which became useless when the network was dropped, the edge empowered classroom continued to operate normally. The table gives a comparison of the two and can be seen in Table 2: Educational Edge Node vs. Online Platforms - Functional Comparison.

TABLE 2: EDUCATIONAL EDGE NODE VS. ONLINE PLATFORMS - FUNCTIONAL COMPARISON

Feature	Edge Learning Hub	Online Platform
Content Availability (%)	97	62
Internet Required	No	Yes
Sync Frequency	Weekly	Real-time
Device Power Requirement	Low (5V USB)	High (Router + PC)

Regarding scalability, the edge framework is modular, which makes it simple to adopt it elsewhere within the SDG context. The same hardware would be able to be set up to monitor flood conditions, track air quality levels, or telemedical assistance. Training of the locals on how to go about operating the edge interfaces implied a short learning curve. The edge systems were deployed with friendly dashboards that could facilitate the usage of local languages, hence they could be used by non-technical people in rural schools and health centers.

Lastly, the cost-benefit analysis indicated that a considerable decrease in operational costs could be achieved through a change on the cloud-heavy systems to edge-based deployments. The edge model

eliminated the need to pay the high cost of satellite bandwidth, continuously subscribing to cloud services, or even having backup infrastructure, making the recurring cost an estimated 55 percent cheaper [1]. The equipment involved in the technology incorporates open-source software stacks and off-the-shelf microcomputers, and further aids long term affordability and sustainability. High community acceptance was based on the resilience and responsiveness of the system, as a result of which positive feedback was noticed among the users who used to experience quite often outages of digital services before.
The analysis indicates that the edge computing represents a sustainable and viable way towards the realization of digital ambitions connected with the SDGs in remote, low-connectivity areas. It lowers the reliance on cloud resources, guarantees real-time reactions, saves electricity, and creates system independence, hence a perfect structure in application to resilient, inclusive, localized technology installations in underprivileged settings.

V. CONCLUSION

Edge computing will change the world as a promising solution to the SDG application implementation in areas affected by poor connectivity and infrastructure. Decentralization of processing and the ability to make decisions in real-time at the point of data reduces the need to depend on cloud networks and power-hungry transmissions. Results of this research validate the feasibility of edge-based SDG applications in agriculture, health, education, and water management. This strategy, in addition to providing continuity and resilience in the low-resource environments, results in digital inclusion of underserved population.
With the trend of localized intelligence around the world, the direction of future work will be to implement an AI-based predictive model on the edge devices to make those devices more independent. Moreover, a set of policies and finance mechanisms will need to be developed so that to facilitate implementation of edge infrastructure and to sustain it in the rural population. Such technology and sustainable development intersection will not only fill digital divide but also generate resilient self-sufficient ecosystems across the globe.

REFERENCES

1.M. Van Hilten and S. Wolfert, "5G in agri-food - A review on current status, opportunities and challenges," *Computers and Electronics in Agriculture*, vol. 201, p. 107291, Aug. 2022, doi: 10.1016/j.compag.2022.107291.
2.E. N. Sadjadi and R. Fernández, "Challenges and opportunities of agriculture digitalization in Spain," *Agronomy*, vol. 13, no. 1, p. 259, Jan. 2023, doi: 10.3390/agronomy13010259.
3.S. K. Sood, K. S. Rawat, and D. Kumar, "Scientometric analysis of ICT-assisted intelligent control systems response to COVID-19 pandemic," *Neural Computing and Applications*, vol. 35, no. 26, pp. 18829–18849, Jun. 2023, doi: 10.1007/s00521-023-08788-3.
4.S. V. Jaiswal, D. V. L. Hunt, and R. J. Davies, "Construction 4.0: A Systematic Review of its Application in Developing countries," *Applied Sciences*, vol. 14, no. 14, p. 6197, Jul. 2024, doi: 10.3390/app14146197.
5.P. E. Ramírez-Correa, A. M. Mariano, and M. R. Santos, "Digital and Sustainable Education and Social Inclusion: A Bibliometric Review with the Consolidated Meta-Analytical Approach," *Sustainability*, vol. 17, no. 13, p. 5677, Jun. 2025, doi: 10.3390/su17135677.
6.J. Bhanye, "Flood-tech frontiers: smart but just? A systematic review of AI-driven urban flood adaptation and associated governance challenges," *Discover Global Society*, vol. 3, no. 1, Jun. 2025, doi: 10.1007/s44282-025-00190-9.
7.G. Panditrao, R. Bhowmick, C. Meena, and R. R. Sarkar, "Emerging landscape of molecular interaction networks: Opportunities, challenges and prospects," *Journal of Biosciences*, vol. 47, no. 2, Apr. 2022, doi: 10.1007/s12038-022-00253-y.
8.Z. Fang, P. Yue, M. Zhang, J. Xie, D. Wu, and L. Jiang, "A service-oriented collaborative approach to disaster decision support by integrating geospatial resources and task chain," *International Journal of Applied Earth Observation and Geoinformation*, vol. 117, p. 103217, Feb. 2023, doi: 10.1016/j.jag.2023.103217.
9.K. Anderson, B. Ryan, W. Sonntag, A. Kavvada, and L. Friedl, "Earth observation in service of the 2030 Agenda for Sustainable Development," *Geo-spatial Information Science*, vol. 20, no. 2, pp. 77–96, Apr. 2017, doi: 10.1080/10095020.2017.1333230.
10. K. Chaturvedi, A. Matheus, S. H. Nguyen, and T. H. Kolbe, "Securing Spatial Data Infrastructures for Distributed Smart City applications and services," *Future Generation Computer Systems*, vol. 101, pp. 723–736, Jul. 2019, doi: 10.1016/j.future.2019.07.002.
11. L. Chen *et al.*, "An introduction to the Chinese High-Resolution Earth Observation System: GAOFEN-1~7 Civilian satellites," *Journal of Remote Sensing*, vol. 2022, Jan. 2022, doi: 10.34133/2022/9769536.
12. Demir and W. F. Krajewski, "Towards an integrated Flood Information System: Centralized data access, analysis, and visualization," *Environmental Modelling & Software*, vol. 50, pp. 77–84, Oct. 2013, doi: 10.1016/j.envsoft.2013.08.009.

13. F. E. A. Horita, J. P. De Albuquerque, L. C. Degrossi, E. M. Mendiondo, and J. Ueyama, "Development of a spatial decision support system for flood risk management in Brazil that combines volunteered geographic information with wireless sensor networks," *Computers & Geosciences*, vol. 80, pp. 84–94, Apr. 2015, doi: 10.1016/j.cageo.2015.04.001.
14. Somthawinpongsai, C., Zhou, F., Wiwitkunkasem, K., Chanwichian, J., & Xing, J. (2024). Digital Communication Strategies in Promoting Sustainable Agriculture: Organic Products in Central Thailand. Journal of Ecohumanism, 3(8), 2822-2838.
15. Shao, Huimin and Guo, Yihang and Yuan, Wanbao and Tee, Mcxin and Lu, Liangyan and Zhou, Fei, A Study On The Impact of Agricultural Brand Awareness on Purchase Decisions In E-Commerce Platforms. Available at SSRN: https://ssrn.com/abstract=4871054 or http://dx.doi.org/10.2139/ssrn.4871054
16. Abdullah, R., Abdullah, S., & Tee, M. (2014, September). Web-based knowledge management model for managing and sharing green knowledge of software development in community of practice. In *2014 8th. Malaysian Software Engineering Conference (MySEC)* (pp. 210-215). IEEE. DOI: 10.1109/MySec.2014.6986016.
17. Sawangchai, A., Hamid, A. B. A., Raza, M., Somtawinpongsai, C., Chanwichian, J., & Methachartsinthavee, A. (2022). The impact of technological interactions on entrepreneurial marketing initiatives in Thailand Service Industry. Journal of Positive Psychology and Wellbeing, 6(1), 253-266.